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Separation of Players in Teams during Basketball Matches

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Abstract. This paper represents a framework for automatic player separation in teams during basketball matches. Separation is made in images broadcasted via television stations. In them, we have view from only single camera in particular point of time. This makes detection of players and their separation much more difficult. The player detection is based on mixture of non-oriented pictorial structures. After detection we extract image parts that represent player’s jersey. Over that area we calculate histogram on S value from HSV color system. According to top five picks, we cluster players in teams. This approach give us accuracy of 92.38%. Its main advantages are robustness and applicability on the large number of footages from different basketball games without need for additional training and algorithm changes.

Keywords: computer vision, player detection, player separation, clustering.

1. Introduction

Analysis of digital media content represents a technology with constant growth and progress in recent years. Application of this technology can be found in medicine, public security, industry, traffic, sport and many other fields.

The aim of this research is to analyze images from basketball games that are publicly broadcasted via television networks. It includes a wide range of activities from how to identify players, determine their position on the court, recognize ball, hoops, when the player takes the shoot, and weather the shoot was successful or not.

The process of analysis starts with a basketball game footage. From it, we extract video frames. In most common scenario, each second of the footage contains 30 frames. During the analysis, we concluded that it is not necessary to perform analysis on each frame. In this research, we used every third frame, or ten frames per second. This has significant impact on performances without loss of accuracy because no event is happening so fast that it will not be recorded with a reduced set of frames. This set of frames is the starting point for algorithms that will allow player detection and separation in teams.

During the basketball game footages that are distributed view television networks, we often could see shots that do not represent the game itself. Those are mainly scenes of audience, players that are currently on the bench, replay and slow motions of previous actions etc. Since they do not represent the game itself, they need to be removed from the analysis process. Recognition of those frames is done by comparing quantified color histograms. By application of this algorithm, we remove all frames that do not represent court. Frames representing the game are further analyzed in order to determine the court, hoops, ball and the players.

In order to separate players in teams, we first need to recognize them. The player detection is quite a difficult problem. The reason is in basketball game itself, which is a very dynamic sport with players constantly altering in a wide variety of positions and poses. The camera moves from one side of the court to the other and zooms certain moments, so the player's size is not always constant. Secondly, due to players changing an angle in relation to the camera, some body parts may seem foreshorten compared to the others. Also, it happens quite often that a player is to some extent obscured by other players.

2. Related Work

Human motion analysis using computer vision is very widespread. Its attractiveness is based on a wide field of application and great complexity. Complexity represents a challenge in the research, seen from a pure academic point of view [1]. From the point of application, methods based on the computer vision are often only non-invasive solution, which makes them particularly attractive. The process of capturing movements, called human motion capture covers many aspects. It is mainly related to the recording of the obvious movements that man does (movements of the head, arms, torso and legs). Previous definition do not cover body movements of smaller scale such are facial expressions and gestures.

Discriminative methods are dominant in object recognition and sport events analysis. One of the first solution that has been successfully applied in the detection and monitoring of players on sports matches was a BPF (Boosted Particle Filter). Okuma et al. were using BPF in order to track players on hockey matches [2].

The player detection in this paper is done via part-based methods [3]. These methods decompose the appearance of the objects into local part templates, together with geometric constraints on locations of the parts. In this paper we used a mixture of non-oriented pictorial structures [4] which is a very robust algorithm. Beside players, this algorithm detects a player arms, legs, head and torso.

Mixture of non-oriented pictorial structures augments the classic spring models with co-occurrence constraints that favor certain combinations of parts. Such constraints can capture the local rigidity. What it means is that two parts on the same limb should have the same orientation. The key issue is learning such a complex presentation from the training data. As in [4, 5], the solution is in a supervised learning mode. Model training is performed using the player’s images that are labeled in fourteen points (ankles, knees, hips, wrists, elbows, shoulders, chin and scalp). The area around each point represents an instance of specific object category. Detail description of player detection is described in our paper Automatic Player Position Detection in Basketball Games [6].

3. Separation of Players in Teams

When we detect all players on the field, we want to separate them into teams. Applied algorithm is shown by diagram in Fig. 1.

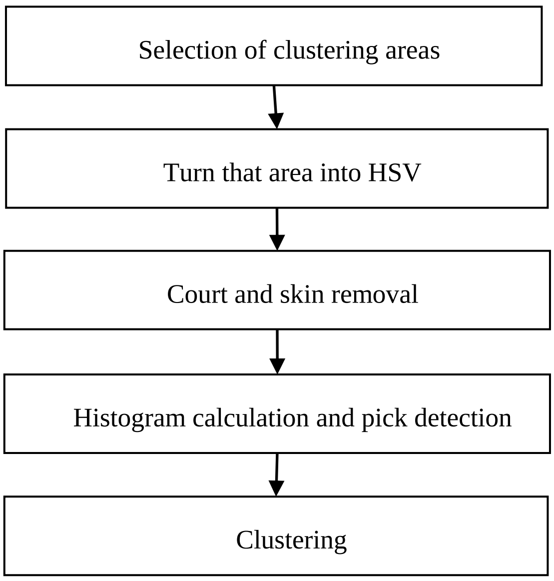

Fig. 1. Algorithm for player separation in teams.

From Fig. 1 we could see that first step is selection of clustering areas. This is selection of those parts that are covered with jersey. In case of basketball players, those are parts 3, 8, 9, 10, 11, 12, 15, 20, 21, 22, 23 and 24. Those parts are marked with red color in Fig 2. All these parts form one area that will be used in further processing. Example of created area is shown in Fig 3.

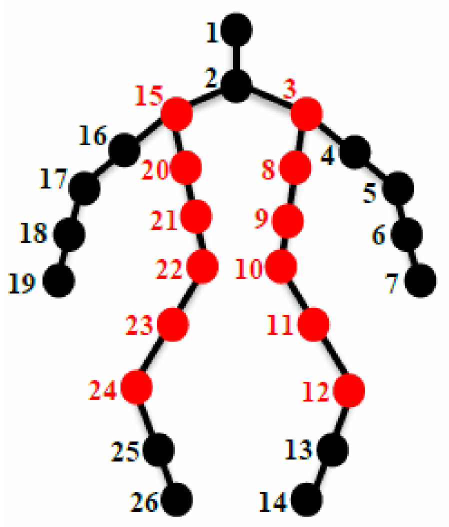

Fig. 2. Selected areas for clustering

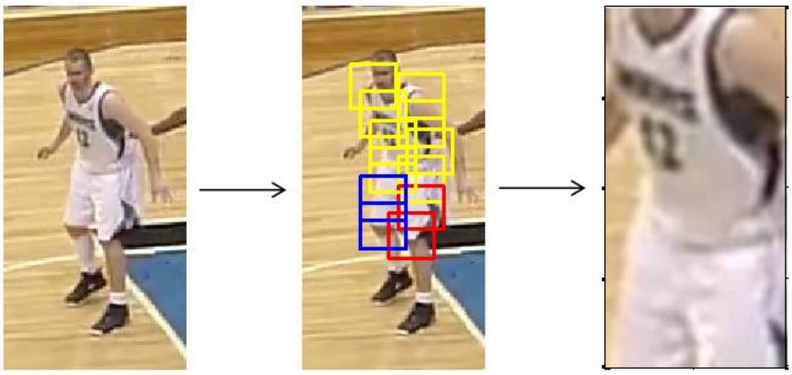

Fig. 3. Creation of clustering area

After clustering area creation, we transform it to HSV color system for two reasons. First reason is the fact that H (Hue) component of this system represents a color. By specifying the scope which contains parquet and player skin, these pixels can be removed from further processing. An example of removal of the skin and parquet flooring, within the clustering area, is shown in Fig. 4. Another reason is that every team in the league has two sets of jerseys. One set is "bright" and the other is "dark". Both sets are designed in accordance with the colors of the team, and in accordance with the previous limit. On any match, the teams are in different types of jerseys (one is in the light set, and the other in the dark). If we observe saturation component S of HSV model, it may be noted that light set has low saturation, while dark set of jerseys has a high saturation. This is exactly the qualities that we used for histogram calculation and team clustering.

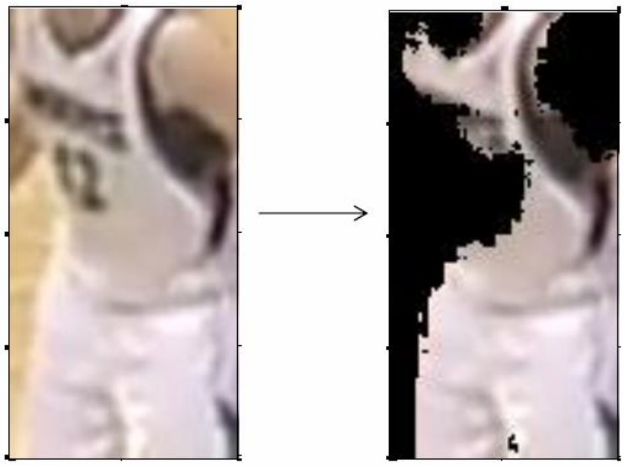

Fig. 4. Removal of skin and parquet pixels from clustering area

The histogram is determined over the saturation component of those pixels within the detection area that does not represent the parquet and skin. We calculate 100-bit histogram, from which we then selects five peaks with the highest value. A similar approach, but in determining the color of the terrain, were used by [7], with the difference that they used H component and the one or two most influential peaks. The reason for extraction of five most influential peaks in our work, lies in the fact that the images are not of the same size and it is not known how much of the image will fall off from further processing as it represents the terrain or skin. The extraction of dominant peaks in saturation histogram is shown in Fig. 5.

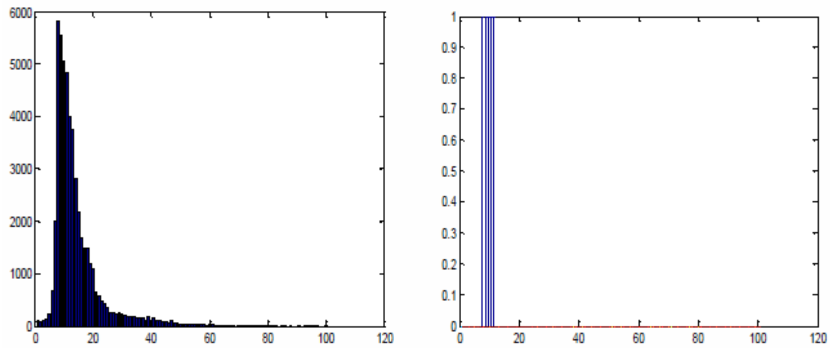

Fig. 5. Removal of skin and parquet pixels from clustering area.

Five peaks in the histogram of each player goes into the process of clustering by k-means basis. Objects belonging to the first cluster are players of a first team, and the objects that belong to another cluster are the players of the second team. By applying this approach, it is not necessary to re-train algorithm for each new team and new color of jerseys. In order to determine which cluster represents which team, we just need to know which team in the observed the game wears light, and which team wears dark set of jerseys. Separation of players by teams is shown in Fig. 6.

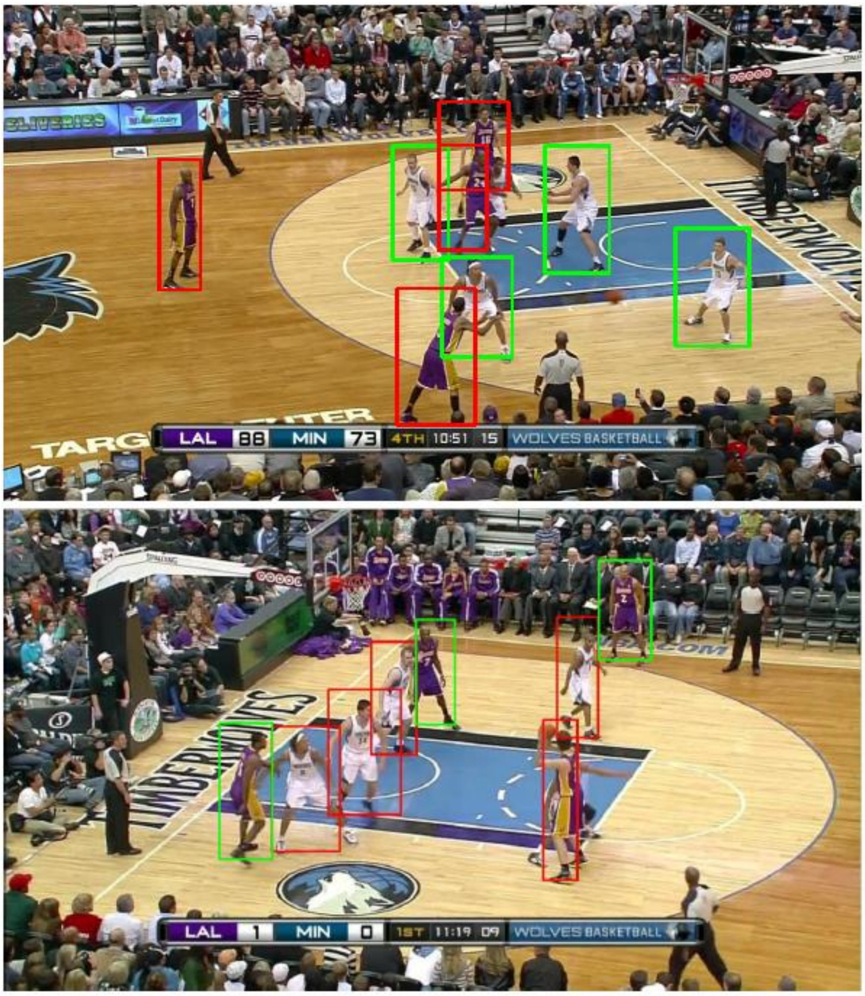

Fig. 6. Separation of players by teams.

4. Experimental results

When we complete the process of players' recognition, the goal is to separate them into teams based on the color of their jerseys. The algorithm was tested on a set that consists of 100 frames from ten different NBA basketball games. Results of player separation based on jersey colors are shown in Table 1. From the table it can be seen that from a total of 748 players identified, the algorithm correctly classified by teams 691 players representing an accuracy of 92.38%. The algorithm has demonstrated greater accuracy in players who wear bright uniforms (96.34%), compared with players in dark uniforms (88.21%). The reason for this discrepancy lies in the fact that dark jerseys often have a specific area of bright color on the side. This area can become dominant, especially when the player is not directly facing the camera. From the table it can be seen that the number of incorrectly classified players in dark jerseys is almost three times higher in comparison with players in light jerseys.

Table 1. Player separation by teams.

	Correct classifications	Incorrect classifications	%
Light jerseys	369	14	96.34
Dark jerseys	322	43	88.21
Total	691	57	92.38

5. Conclusion

The presented algorithms represent a step forward for the process of automatic separation of players in teams. Separation is done on basketball game footages broadcasted via TV stations. This type of footage, at any point of time, can provide a view from only one camera, which makes a detection process much harder. Its main contribution is robustness and applicability on the large number of footages from different basketball games without need for additional training and algorithm changes. Space for further investigation is very broad. It includes the determination of the player’s jersey number in order to accomplish its identification.

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